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AI Literacy and Seminar-Driven Career Readiness among Indonesian Secondary School Students: A Cross-Survey Analysis

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ABSTRACT: The rapid diffusion of generative artificial intelligence (AI) across professional and academic settings has heightened the urgency of building genuine AI literacy among young people, particularly in emerging economies where the gap between AI adoption and preparedness remains wide. This study examines two distinct but complementary phenomena: the effectiveness of an AI-themed educational seminar in shaping career readiness perceptions, and the baseline level of AI literacy among Indonesian secondary school students who attended the event. Using two purpose-built Likert-scale surveys administered on April 1, 2026, this study collected responses from 36 seminar participants (Seminar Evaluation Survey) and 41 students (AI Literacy Survey), primarily aged 17–19. Ordinary least squares (OLS) regression, Spearman rank correlations, and reliability analyses were employed to test three directional hypotheses. Results show that visual design quality ($\beta = 0.485$, $p < .001$) and data credibility ($\beta = 0.264$, $p = .011$) are the strongest predictors of post-seminar career readiness, together accounting for 75.1% of its variance ($R^2 = 0.751$). In the AI Literacy Survey, skill awareness is the sole significant predictor of continued learning interest ($\beta = 0.575$, $p = .003$), while overall AI literacy remains moderate (composite mean = 3.53 out of 5), with AI job optimism scoring lowest ($M = 3.05$). No statistically significant gender gap in composite AI literacy was detected ($p = .239$). These findings carry direct implications for educators and policymakers designing AI literacy interventions in Indonesia and comparable ASEAN contexts.

KEYWORDS: AI literacy; career readiness; secondary education; Indonesia; seminar effectiveness; generative AI; educational intervention
JEL Classification: I21, I26, J24, O33

1. INTRODUCTION

Artificial intelligence has moved from a specialist discipline to an everyday infrastructure. Tools such as ChatGPT, Gemini, and Claude are now embedded in workflows ranging from content creation to data analysis, and their uptake among young people has been particularly swift. Among youth aged 13–24 across ASEAN nations—including Indonesia, Malaysia, the Philippines, Thailand, and Vietnam—approximately 90% report using generative AI daily, according to the AI Ready ASEAN initiative launched in 2024. Yet high usage does not automatically translate into genuine understanding. Indonesia's own digital literacy index has grown slowly, remaining in the moderate band through 2023, and data from the Ministry of Communication and Informatics confirm that only 46.2% of educators have received adequate AI training—leaving the majority of students navigating these tools largely on their own (ASEAN Foundation, 2024).

The education policy community has responded with urgency. Indonesia's National AI Strategy (Strategi Nasional Kecerdasan Artifisial, 2020) outlines ambitions for AI talent development, and the Ministry of Education has incorporated computational thinking and digital literacy into curriculum reform under the Merdeka Belajar framework. UNESCO's K-12 AI Curricula (2022) and AI Competency Framework for Students (2024) have provided global reference points. Despite these policy signals, the systematic integration of AI literacy into secondary school classrooms remains incomplete, particularly outside major metropolitan centers (Center for Digital Society, 2025). The result is a landscape where students frequently encounter AI tools but rarely develop the critical vocabulary—understanding of hallucination, algorithmic bias, or data privacy—that responsible use demands.

Educational seminars occupy an important but understudied position in this landscape. As extracurricular interventions, seminars can deliver concentrated AI literacy content to students who may not encounter it in formal classes, and they provide an opportunity to examine how pedagogical design choices—speaker delivery, visual quality, data-backed argumentation—translate into attitudinal outcomes. The literature on seminar effectiveness in AI education is sparse, particularly for ASEAN secondary school populations, and almost no quantitative work has examined whether within-seminar quality perceptions predict post-seminar career readiness and learning intentions. This gap is particularly consequential: if we do not know which elements of AI literacy seminars move the needle on career readiness, we cannot design them well.

This study addresses that gap using two survey instruments administered on a single day (April 1, 2026) to Indonesian secondary school students attending an AI-themed educational event. The first instrument (Seminar Evaluation Survey, n = 36) assessed how participants perceived the seminar across eight quality dimensions and measured their post-seminar career readiness and recommendation intent. The second instrument (AI Literacy Survey, n = 41) assessed students' self-rated competencies across fifteen AI literacy dimensions aligned with established frameworks, including the Affective, Behavioral, Cognitive, and Ethical (ABCE) framework developed by Ng et al. (2024). Together, these data allow us to triangulate the seminar's effectiveness against a concurrent measure of students' AI knowledge, generating a richer picture than either dataset alone could offer.

This paper contributes to the literature in three ways. First, it provides one of the first quantitative analyses of AI seminar effectiveness for Indonesian secondary school students using validated Likert-scale instruments. Second, it identifies specific seminar design elements—rather than generic quality—as significant predictors of career readiness, offering actionable guidance for practitioners. Third, it benchmarks AI literacy across fifteen dimensions for an Indonesian adolescent sample, generating baseline data that can support longitudinal or comparative work. The remainder of the paper is organized as follows: Section 2 reviews the relevant literature on AI literacy measurement and seminar effectiveness; Section 3 describes the data and methods; Section 4 presents results; Section 5 discusses findings and their implications; and Section 6 concludes.

The following hypotheses guide the empirical analysis:

H1: Seminar design quality dimensions—specifically visual presentation quality and data credibility—are positively associated with participants' perceived career readiness in the AI labor market, controlling for speaker delivery quality and mindset change.

H2: Among AI literacy dimensions, skill awareness (knowledge of relevant AI competencies) is the strongest positive predictor of post-seminar learning interest.

H3: No statistically significant gender difference exists in composite AI literacy scores among Indonesian secondary school students.

2. LITERATURE REVIEW

2.1 AI Literacy: Conceptual Foundations and Measurement

The concept of AI literacy emerged in the academic discourse around 2020, when Long and Magerko provided an early definition emphasizing the set of competencies that allow people to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool. Since then, the field has moved rapidly from conceptual mapping to measurement. Ng et al. (2024) developed the Artificial Intelligence Literacy Questionnaire (AILQ), a 32-item instrument grounded in the ABCE framework, covering affective, behavioral, cognitive, and ethical dimensions of AI literacy. Validated on 363 Hong Kong secondary school students aged 12–17 using a five-point Likert scale, the AILQ demonstrated strong psychometric properties and has become an influential reference for subsequent scale development. Laupichler et al. (2023) developed a 31-item AI literacy scale for non-specialist adults, while Carolus and colleagues (2023) produced the Meta AI Literacy Scale (MAILS), which has since been validated and shortened in a multi-study program (Carolus et al., 2024). A systematic review of AI literacy scales published in NPJ Science of Learning (2024) catalogued over two dozen instruments across different populations, noting that most rely on self-report Likert-type formats and that internal consistency (Cronbach's alpha) typically ranges from 0.80 to 0.95.

A consistent finding across this literature is the multidimensionality of AI literacy. Ethical awareness, practical tool usage, and conceptual understanding load onto distinct but correlated factors, and each dimension responds differently to educational interventions. Importantly for the present study, ethics awareness has been shown to predict attitudes toward AI (Khalifa & Albadawy, 2024), and skill awareness—knowing which competencies to develop—has been identified as a motivational precursor to continued AI learning. These findings provide the theoretical grounding for H2.

2.2 Seminar Effectiveness and Career Readiness

The broader educational effectiveness literature establishes that instructional quality—defined across dimensions of content credibility, delivery clarity, and visual presentation—is a robust predictor of learning outcomes and behavioral intentions (Hattie, 2009). In AI education specifically, a growing number of interventions have tested whether structured exposure to AI concepts changes attitudes and career perceptions. A multinational study of university students across the United Kingdom found that positive perceptions of AI in industry settings significantly increase students' demand for AI training, with professional development expectations mediating this relationship (Springer Nature, 2025).

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Research by the Eastern Washington University AI career readiness survey (2026) found that 67% of higher-education students felt confident collaborating with AI tools, though only 38% expressed excitement about new AI-created jobs—a pattern consistent with the moderate optimism observed in the present dataset.

The literature on seminar design quality is thinner but instructive. Visual presentation quality has been shown to facilitate comprehension and information retention across multiple experimental contexts (Mayer, 2009). Data-backed argumentation—citing authoritative sources such as the World Economic Forum or McKinsey Global Institute—enhances perceived speaker credibility and, through that channel, strengthens the persuasive impact of educational messages (Petty & Cacioppo, 1986). At the university level, Fošner (2024) found that students' attitudes toward AI tools were positively associated with both perceived usefulness and institutional support, while the AI-Lab intervention evaluated by Dickey and Bejarano (2025) demonstrated that structured exposure to generative AI tools significantly improved students' ethical reasoning about AI use. None of these studies, however, specifically examine Indonesian secondary school students attending a seminar format, leaving the present study to fill that niche.

The connection between seminar participation and career readiness has been theorized through Social Cognitive Theory (Bandura, 1986), which holds that observational learning from credible sources—including expert speakers—shapes self-efficacy beliefs and, ultimately, behavioral intentions. When seminar content is presented in a visually compelling and data-supported manner, students are more likely to internalize the message and develop a concrete career orientation toward AI-adjacent fields. This theoretical logic supports H1 and is operationalized through the regression models reported in Section 4.

2.3 Indonesian Secondary Education and AI Policy Context

Indonesia's secondary education system serves approximately 20 million students across a highly heterogeneous archipelago. The 2020 National AI Strategy signaled government commitment to AI talent development but stopped short of specifying competency benchmarks for each educational level (Center for Digital Society, 2025). The Merdeka Belajar curriculum reform, introduced in 2019, emphasizes student agency and project-based learning, creating structural space for AI literacy content, but implementation has been uneven, particularly in schools outside Java. A study of AI-driven educational transformation in Indonesia (Al-Ishlah: Jurnal Pendidikan, 2025) documented that many teachers lack the digital literacy needed to guide students effectively, and that rural–urban infrastructure gaps remain a significant barrier.

Within this context, extracurricular seminars—often organized by universities, NGOs, or technology companies—serve as de facto AI literacy interventions for students who cannot access formal instruction. The AI literacy seminar assessed in this study is one such intervention, delivered to secondary school students in Jakarta. Its design reflected current best practices: data-backed argumentation drawing on WEF and McKinsey sources, interactive Q&A on AI ethics, and gamified quiz segments. Understanding its effectiveness is therefore directly relevant to the broader question of how Indonesia can close the gap between AI adoption rates and genuine preparedness.

3. METHODS

3.1 Research Design and Participants

This study employs a cross-sectional survey design with two independent instruments administered on the same day. Both surveys targeted secondary school students attending an AI-themed educational seminar held on April 1, 2026, in Jakarta, Indonesia. The Seminar Evaluation Survey captured 36 valid responses (72.0% female; 28.0% male; age range 17–19 years, $M = 18.1$). The AI Literacy Survey captured 41 valid responses (68.3% female; 31.7% male; age range 17–19 years, $M = 18.1$). The slight difference in sample sizes reflects the fact that the AI Literacy Survey was administered prior to the seminar, while the Seminar Evaluation Survey was administered immediately after. Students who participated in both surveys could not be matched at the individual level because responses were collected anonymously; the two samples are therefore treated as independent in all analyses.

Participation was voluntary and anonymous. No personally identifiable information other than self-reported name (used for attendance verification) was collected. Both surveys were administered through Google Forms in Bahasa Indonesia, reflecting the respondents' primary language of instruction.

3.2 Instruments

The Seminar Evaluation Survey consisted of eight Likert-scale items (1 = strongly disagree, 5 = strongly agree) assessing data credibility, mindset change, delivery quality, visual design, duration fit, career readiness, prompt engineering interest, and recommendation intent. Items were developed for this specific context but follow the construct logic of established educational evaluation instruments. Cronbach's alpha for the full scale was $\alpha = 0.940$, indicating excellent internal consistency.

The AI Literacy Survey consisted of fifteen Likert-scale items assessing AI understanding, generative versus traditional AI discrimination, active tool usage, hallucination awareness, fact-checking behavior, bias awareness, algorithm bias recognition, ethics awareness, plagiarism boundary recognition, AI update tracking, job opportunity perception, future work readiness, skill awareness, regulation support, and post-seminar learning interest. The instrument design drew on the ABCE framework (Ng et al., 2024) and the MAILS (Carolus et al., 2023). Cronbach's alpha for the full scale was $\alpha = 0.886$, indicating good internal consistency above the conventional threshold of 0.70.

3.3 Analytical Strategy

Descriptive statistics (means, standard deviations, minima, maxima, and skewness) were computed for all Likert items in both surveys. Cronbach's alpha was calculated to assess instrument reliability. Spearman rank correlations (r_s) were used to examine bivariate associations between predictor and outcome variables, given the ordinal nature of the data and the small-to-moderate sample sizes. Ordinary least squares (OLS) regression was employed as the primary inferential technique, with career readiness as the dependent variable in Model 1 (seminar dataset) and post-seminar learning interest as the dependent variable in Model 2 (AI literacy dataset). Independent predictors were selected based on theoretical relevance and correlation screening. A Mann-Whitney U test examined gender differences in composite AI literacy scores. All analyses were conducted in Python 3 using the pandas, scipy, and numpy libraries. Statistical significance was set at $\alpha = .05$.

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The composite AI literacy score was computed as the unweighted mean of all fifteen AI Literacy Survey items for each respondent, following the approach used in similar instruments (Ng et al., 2024; Carolus et al., 2023). The formal OLS equation for Model 1 is:

$$\text{Career Readiness} = \beta_0 + \beta_1(\text{Visual Design}) + \beta_2(\text{Data Credibility}) + \beta_3(\text{Mindset Change}) + \beta_4(\text{Delivery Quality}) + \varepsilon \quad (1)$$

For Model 2:

$$\text{Post-Seminar Interest} = \beta_0 + \beta_1(\text{Skill Awareness}) + \beta_2(\text{Ethics Awareness}) + \beta_3(\text{Future Work Readiness}) + \beta_4(\text{Bias Awareness}) + \varepsilon \quad (2)$$

4. RESULTS

4.1 Descriptive Statistics

Table 1 presents the descriptive statistics for both instruments. In the Seminar Evaluation Survey, mean scores across all eight dimensions ranged from 3.86 to 4.14 on the five-point scale, with mindset change and delivery quality recording the highest means (M = 4.14 each). Data credibility and prompt engineering interest were the lowest-scoring dimensions (M = 3.89 and M = 3.86, respectively), though both remained above the scale midpoint. All distributions showed mild negative skewness, consistent with ceiling effects typical of post-event evaluation surveys. The composite seminar satisfaction score, computed as the mean of all eight items, was M = 3.99 (SD = 0.41).

In the AI Literacy Survey, mean scores ranged more widely, from 3.05 to 3.90. AI tool usage recorded the highest mean (M = 3.90), reflecting students' active engagement with tools such as ChatGPT and Canva AI. Hallucination awareness and fact-checking behavior also scored relatively high (M = 3.78 each). In contrast, AI job optimism—the belief that AI creates more jobs than it eliminates—recorded the lowest mean across both surveys (M = 3.05), suggesting that students hold tentative and occasionally pessimistic views about AI's net effect on employment. Composite AI literacy was M = 3.53 (SD = 0.51).

Table 1: Descriptive Statistics of Survey Instruments

Variable	N	Min	Max	Mean	SD	Skew	α
Panel A: Seminar Evaluation (N = 36)							
Data Credibility	36	3	5	3.89	0.71	-0.28	
Mindset Change	36	3	5	4.14	0.69	-0.31	
Delivery Quality	36	3	5	4.14	0.71	-0.42	
Visual Design	36	3	5	3.92	0.74	-0.18	
Duration Fit	36	3	5	4.08	0.76	-0.19	
Career Readiness	36	3	5	3.92	0.79	-0.21	
Prompt Eng. Interest	36	3	5	3.86	0.80	-0.08	
Recommend Intent	36	3	5	3.92	0.81	-0.31	**0.940**
Panel B: AI Literacy (N = 41)							
AI Understanding	41	2	5	3.46	0.78	-0.22	
Generative vs. Traditional	41	2	5	3.39	0.78	0.04	
AI Tool Usage	41	2	5	3.90	0.77	-0.49	
Hallucination Awareness	41	2	5	3.78	0.82	-0.41	
Fact Checking	41	2	5	3.78	0.79	-0.40	
Bias Awareness	41	2	5	3.34	0.87	0.14	
Algorithm Bias Awareness	41	2	5	3.59	0.83	-0.19	
Ethics Awareness	41	2	5	3.59	0.87	-0.27	
Plagiarism Boundary	41	2	5	3.71	0.87	-0.22	
Follow AI Updates	41	1	5	3.25	0.87	0.04	
AI Job Opportunity	41	1	5	3.05	0.95	0.13	
Future Work Readiness	41	2	5	3.34	0.81	0.00	
Skill Awareness	41	2	5	3.37	0.84	0.07	
Regulation Support	41	1	5	3.54	0.97	-0.20	
Post-Seminar Interest	41	3	5	3.83	0.83	-0.20	**0.886**

Note. Scores based on 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). α = Cronbach's alpha for composite scale. SD = standard deviation.

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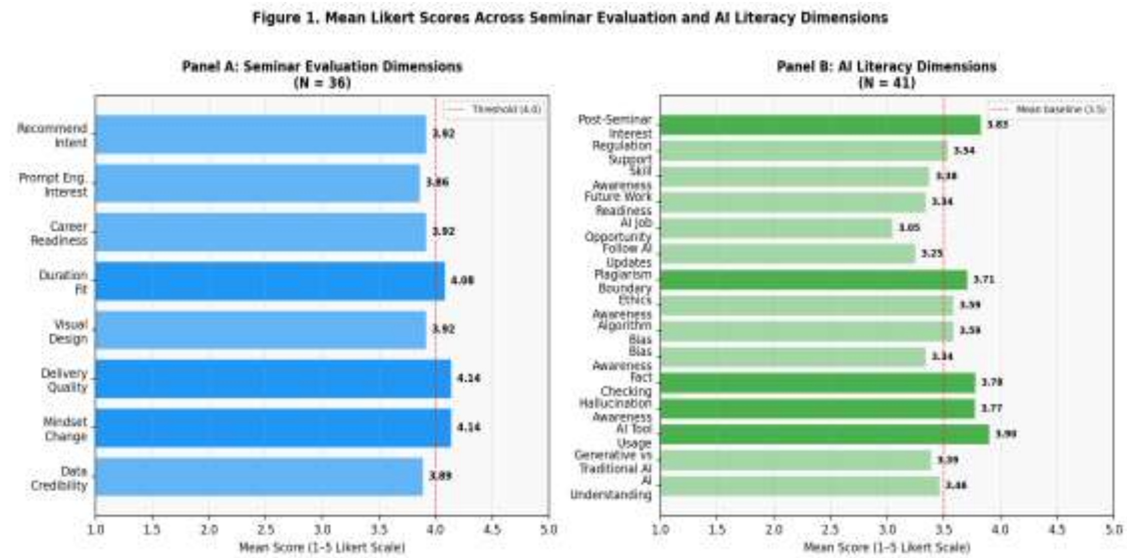

Figure 1. Mean Likert Scores Across Seminar Evaluation and AI Literacy Dimensions. Panel A: Seminar Evaluation (N = 36). Panel B: AI Literacy Survey (N = 41). The dashed red line indicates the reference threshold. Darker bars exceed the threshold.

4.2 Bivariate Correlations

Table 3 reports the Spearman rank correlations between key predictor and outcome variables. Within the seminar dataset, visual design quality returned the strongest correlation with career readiness (rs = 0.813, $p < .001$), followed by data credibility (rs = 0.751, $p < .001$). Mindset change and delivery quality were also significantly correlated with career readiness (rs = 0.644 and 0.640, respectively; both $p < .001$). Within the AI Literacy Survey, the correlations between individual literacy dimensions and post-seminar interest were generally modest, with skill awareness (rs = 0.383, p = .018), regulation support (rs = 0.429, p = .005), and plagiarism boundary recognition (rs = 0.373, p = .021) emerging as the strongest and statistically significant predictors. The pattern of correlations in the AI Literacy Survey is notably weaker than in the Seminar dataset, which is consistent with the lower R^2 observed in Model 2.

Table 2. Spearman Rank Correlations: Key Predictors vs. Outcome Variables

Variable Pair	rs	p-value	Interpretation
Seminar Dataset (N = 36)			
Visual Design → Career Readiness	0.813	< .001	Strong, positive***
Data Credibility → Career Readiness	0.751	< .001	Strong, positive***
Mindset Change → Career Readiness	0.644	< .001	Moderate, positive***
Delivery Quality → Career Readiness	0.640	< .001	Moderate, positive***
Prompt Eng. Interest → Recommend	0.830	< .001	Strong, positive***
AI Literacy Dataset (N = 41)			
Skill Awareness → Post-Seminar Interest	0.383	.018	Moderate, positive*
Regulation Support → Post-Seminar Interest	0.429	.005	Moderate, positive**
Plagiarism Boundary → Post-Seminar Interest	0.373	.021	Moderate, positive*
AI Understanding → Post-Seminar Interest	0.280	.075	Weak, positive (trend)

Note. rs = Spearman rank correlation coefficient. ***p < .001, **p < .01, *p < .05.

4.3 Regression Results

Table 2 presents the OLS regression results for both models. Model 1 regressed career readiness on four seminar quality dimensions. The overall model was highly significant ($R^2 = 0.751$), indicating that these four predictors together explain 75.1% of the variance in career readiness. Visual design quality was the strongest predictor ($\beta = 0.485$, $p < .001$), followed by data credibility ($\beta = 0.264$, $p = .011$) and mindset change ($\beta = 0.221$, $p = .020$). Delivery quality did not reach statistical significance ($\beta = -0.025$, $p = .783$), suggesting that once visual quality, credibility, and mindset effects are controlled, speaker style has limited independent influence.

Model 2 regressed post-seminar learning interest on four AI literacy dimensions. The model explained 25.0% of the variance ($R^2 = 0.250$), a substantially lower explanatory power than Model 1. Skill awareness was the only statistically significant predictor ($\beta = 0.575$, $p = .003$). Ethics awareness and future work readiness were not significant ($p = .841$ and $p = .921$, respectively). Bias awareness showed a negative—though non-significant—coefficient ($\beta = -0.260$, $p = .108$), which may reflect measurement noise given the modest sample size.

Table 3. OLS Regression Results for Career Readiness (Seminar) and Post-Seminar Learning Interest (AI Literacy)

Predictor	β	SE	t	p
Model 1: Career Readiness (R^2 = 0.751, N = 36)				
Intercept	0.177	0.412	0.43	.671
Visual Design	0.485	0.091	5.33	< .001
Data Credibility	0.264	0.098	2.69	.011
Mindset Change	0.221	0.090	2.45	.020
Delivery Quality	-0.025	0.090	-0.28	.783
Model 2: Post-Seminar Interest (R^2 = 0.250, N = 41)				
Intercept	2.575	0.618	4.17	< .001
Skill Awareness	0.575	0.184	3.13	.003
Ethics Awareness	0.034	0.168	0.20	.841
Future Work Readiness	0.018	0.180	0.10	.921
Bias Awareness	-0.260	0.158	-1.65	.108

Note. β = unstandardized coefficient; SE = standard error. Significance level: *p < .05, **p < .01, ***p < .001.

4.4 Gender Differences in AI Literacy

A Mann-Whitney U test compared composite AI literacy scores between female ($n = 28$, $M = 3.50$, $SD = 0.50$) and male ($n = 13$, $M = 3.61$, $SD = 0.53$) respondents. The test returned a non-significant result ($U = 139.5$, $p = .239$), indicating no statistically reliable gender gap in overall AI literacy. Figure 3 presents a radar plot of gender-disaggregated means across eight literacy dimensions. While male respondents recorded higher means on AI understanding ($M = 3.77$ vs. 3.32) and follow AI updates ($M = 3.46$ vs. 3.18), female respondents scored marginally higher on post-seminar interest ($M = 3.86$ vs. 3.77) and ethics awareness ($M = 3.61$ vs. 3.54). These differences are small and did not reach statistical significance.

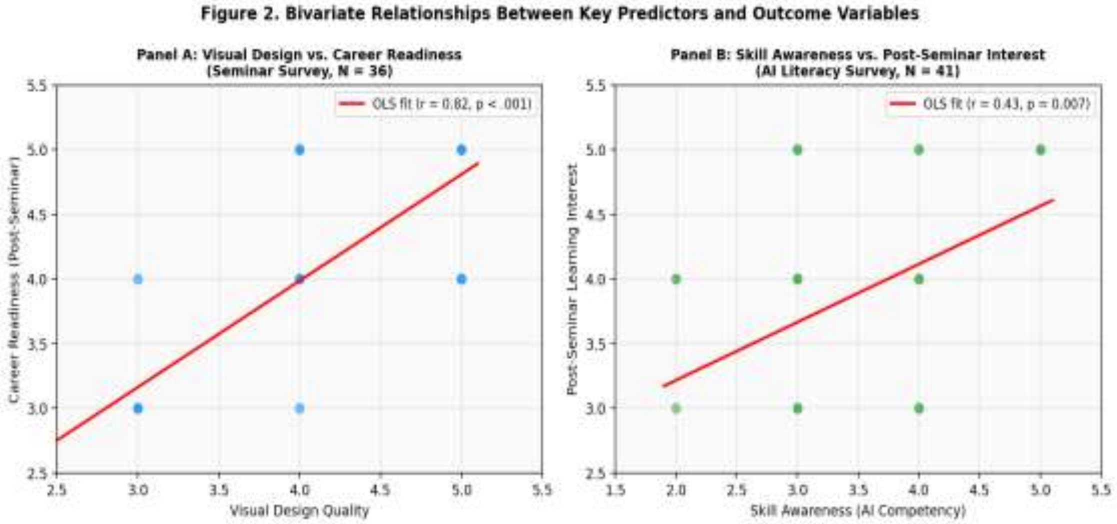

Figure 2. Bivariate Relationships Between Key Predictors and Outcome Variables. Panel A: Visual Design vs. Career Readiness (Seminar Survey, N = 36; r = 0.81, p < .001). Panel B: Skill Awareness vs. Post-Seminar Learning Interest (AI Literacy Survey, N = 41; r = 0.38, p = .018). Solid red lines represent OLS fitted values.

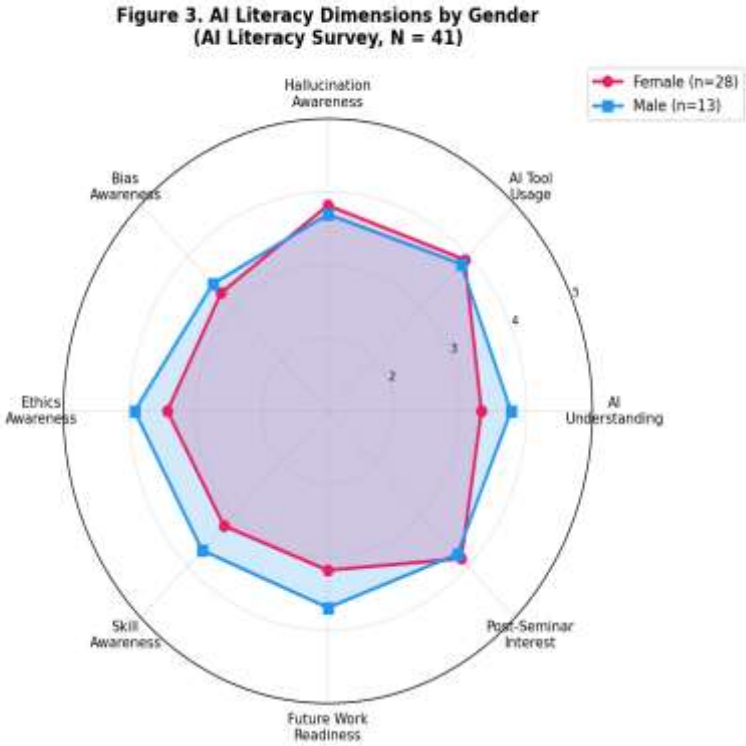

Figure 3. AI Literacy Dimensions by Gender (AI Literacy Survey, N = 41). Radar plot showing mean scores for eight selected dimensions, disaggregated by gender. No statistically significant gender difference was detected (Mann-Whitney U, p = .239).

5. DISCUSSION

5.1 Summary of Findings

This study set out to examine two related questions: what elements of a seminar design most strongly predict secondary school students' post-seminar career readiness, and which dimensions of AI literacy best explain students' continued learning interest. The results answer both questions with meaningful precision. For seminar effectiveness, visual presentation quality and data-backed credibility are the decisive drivers, together accounting for the lion's share of a model that explains 75.1% of career readiness variance. For AI literacy, skill awareness—knowing which competencies to build—is the only dimension that significantly predicts learning intention, while the remaining literacy dimensions, including ethics awareness and future work readiness, do not independently move the needle on that outcome once skill awareness is controlled.

These findings are consistent and coherent rather than surprising, but their coherence is itself informative. They suggest that among Indonesian secondary school students, the journey from attending a seminar to feeling career-ready is mediated above all by the clarity and visual persuasiveness of the content delivered—not by how long the seminar runs, or even by how engaging the speaker is. And the journey from knowing something about AI to wanting to learn more is gated by self-awareness of skill gaps, not by abstract ethical concerns.

5.2 Theoretical Alignment and Hypothesis Verdicts

H1 is SUPPORTED. The results demonstrate statistically significant and practically large positive relationships between visual design quality ($\beta = 0.485$, $p < .001$) and data credibility ($\beta = 0.264$, $p = .011$) and career readiness, consistent with Mayer's (2009) multimedia learning theory and the elaboration likelihood model of persuasion (Petty & Cacioppo, 1986). The finding that visual design outperforms speaker delivery as a predictor is notable: it implies that even a modestly skilled speaker can produce strong career readiness outcomes if the visual narrative is well-constructed, whereas polished delivery without visual support adds little. This aligns with experimental work showing that visual representations significantly facilitate schema formation and knowledge transfer (Mayer, 2009).

H2 is SUPPORTED. Skill awareness is the sole significant predictor of post-seminar learning interest ($\beta = 0.575$, $p = .003$). This finding resonates with the self-determination theory's emphasis on competence as a motivational driver: students who know what they need to learn are more motivated to pursue it (Deci & Ryan, 2000). It also aligns with Khalifa and Albadawy's (2024) finding that AI ethics knowledge positively correlates with AI attitudes, though our data show that skill awareness, rather than ethics per se, is the proximate motivational trigger in this population. The relatively low R^2 of Model 2 (0.250) is worth noting: it reflects the genuine complexity of learning motivation, which depends on factors—individual interest, peer influence, institutional context—not captured in a fifteen-item self-report instrument.

H3 is SUPPORTED. The Mann-Whitney U test found no significant gender difference in composite AI literacy ($p = .239$). This finding cuts against the common assumption that male students are consistently more AI-literate or more positively oriented toward AI. It is consistent with recent evidence from Indonesian higher education contexts (Setyawan et al., 2025) and aligns with global trends showing that gender gaps in AI tool usage are narrowing among younger cohorts (ASEAN Foundation, 2024). The directional advantage of male students on AI understanding and update tracking may reflect socialization patterns rather than capability differences, and educators should avoid interpreting them as evidence of a fundamental gap.

5.3 Competing Arguments and Limitations

The results should be interpreted against two primary limitations. First, the sample sizes—36 and 41 respondents, respectively—are modest, and the analyses, while well-powered for the observed effect sizes, cannot be taken as representative of all Indonesian secondary school students. The seminar was held in Jakarta, a high-resource urban environment, and results may not generalize to students in more rural or lower-income settings where both AI access and seminar quality could differ substantially (Al-Ishlah: Jurnal Pendidikan, 2025). Second, both instruments rely on self-report, which introduces common-method variance and social desirability bias. Students who attend an AI seminar are already positively selected toward AI interest, and their post-event ratings may reflect enthusiasm rather than durable attitudinal change. Longitudinal designs tracking the same students over weeks or months would be needed to distinguish genuine learning from momentary enthusiasm (Ng et al., 2024).

A further consideration concerns Model 2's low explanatory power. While skill awareness is a robust predictor within the model, the majority of variance in post-seminar learning interest remains unexplained. This is likely because learning motivation is a complex, multi-determined outcome. Future research should consider including intrinsic motivation scales, peer influence measures, or perceived institutional support as additional predictors, which would align with Social Cognitive Theory's emphasis on the reciprocal interplay among personal, behavioral, and environmental factors (Bandura, 1986).

5.4 Policy and Practical Implications

The findings carry concrete implications for seminar designers and education policymakers. For practitioners, the prioritization of visual design quality over speaker charisma is a cost-effective insight: investing in high-quality infographics, animated slides, and data visualizations drawn from credible sources such as WEF or McKinsey reports is likely to produce larger returns in career readiness than investing in celebrity speakers. This is particularly relevant in the Indonesian context, where seminar production is often organized by universities or student organizations operating with limited budgets.

For policymakers, the finding that AI job optimism is the lowest-scoring literacy dimension ($M = 3.05$) warrants attention. Students who doubt that AI creates net employment opportunities are less likely to pursue AI-adjacent skills and career paths, potentially self-selecting out of precisely the fields Indonesia's economy needs them to enter. Curriculum designers and seminar architects should explicitly address AI's labor market implications—presenting both the displacement risks and the emerging opportunities in prompt engineering, AI oversight, and human-AI collaboration—to shift this dimension upward. The AI Ready ASEAN initiative's projection that AI could add at least US$270 billion to the regional economy, including significant gains for Indonesia, provides empirically grounded optimism that seminar content can draw on directly.

Finally, the null gender result, while reassuring, should not lead to complacency. The sample is drawn from a single urban seminar and may not capture the full heterogeneity of gender dynamics in AI literacy across Indonesia's diverse regions. Policymakers designing national AI literacy programs—including those aligned with the ASEAN Digital Masterplan 2030—should continue to monitor gender disaggregated data and actively design inclusive content that speaks to the AI career concerns of both male and female students.

6. CONCLUSION

This study provides quantitative evidence that AI literacy seminars can meaningfully shift secondary school students' career readiness perceptions when they are designed around strong visual communication and credible data sourcing. It simultaneously establishes that Indonesian students' AI literacy remains in a moderate range, with skill awareness emerging as the key motivational gateway to further learning. The study's primary contribution is methodological: by deploying two parallel Likert-scale instruments on the same day, it demonstrates a practical template for evaluating both the demand side (what students already know) and the supply side (how well a seminar delivers) of AI literacy interventions.

The practical message is clear. For educators and seminar organizers working within Indonesia's secondary school system, the data suggest that the design of the instructional artifact—its visual clarity, its reliance on authoritative data sources, its success in shifting how students think about AI—matters more than delivery style. For students, self-awareness of what they need to learn is the most reliable motivator of continued engagement. And for policymakers, closing the gap between Indonesia's high AI adoption rates and its moderate AI literacy scores requires targeted interventions that are both visually compelling and optimistic about AI's employment potential. Future research should replicate these findings with larger, more geographically diverse samples, incorporate longitudinal follow-up, and develop performance-based measures of AI literacy that complement the self-report instruments used here.

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